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Dissertation Chapter 3

Technology Use and Worker Outcomes: Direct Evidence from Linked Employee-Employer Data

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ABSTRACT

We investigate the impact of technology adoption on workers' wages and mobility in U.S. manufacturing plants by constructing and exploiting a unique Linked Employee-Employer data set containing longitudinal worker and plant information. We first examine the effect of technology use on wage determination, and find that technology adoption does not have a significant effect on high-skill workers, but negatively affects the earnings of low-skill workers after controlling for worker-plant fixed effects. This result seems to support the skill-biased technological change hypothesis. We next explore the impact of technology use on worker mobility, and find that mobility rates are higher in high-technology plants, and that high-skill workers are more mobile than their low and medium-skill counterparts. However, our technology-skill interaction term indicates that as the number of adopted technologies increases, the probability of exit of skilled workers decreases while that of unskilled workers increases.

I. INTRODUCTION

What is the effect of technology adoption on worker mobility and wages? It is a well known and documented fact that the skill-level wage differential has widened in the last several decades. One of the hypothesis that has received more attention by economists is that the observed changes are likely the result of the introduction of skill biased technologies in the production process (Bound and Johnson (1992), Davis and Haltiwanger (1991), Sachs and Shatz (1994)). If new technologies and skilled labor are complements, then the implementation of new technologies in the workplace will increase the demand for skilled workers relative to unskilled workers, therefore increasing their relative wage.

A variety of studies have examined whether technological change in the U.S. is indeed technically biased. Berndt, Morrison and Rosenblum (1992), Berman, Bound and Griliches (1994), and Autor, Katz and Krueger (1996) model changes in workforce skill as a function of changes in industry capital intensity and industry-level investment in computer equipment. All of them find evidence that capital and skill are complements and that there exists a positive correlation between changes in the skill of workers in an industry and the level of computer investment in the industry. Krueger (1993) uses cross-sectional worker data and finds that workers using computers are better paid than non-users. Dunne and Schmitz (1995) using plant-level data show that workers employed in establishments that use more technologies are paid higher wages. On the other hand, in their longitudinal study Doms, Dunne and Troske (1997) using U.S. plant-level data find no correlation between technology adoption and worker wages, and conclude that most technologically advanced plants pay higher wages both pre and post adopting new technologies. In France, Entorf, Gollac and Kramarz (1997) examine the validity of the skill-biased technological change hypothesis using french longitudinal data on workers and firms. Similarly to Doms *et al*. (1997), they find that workers that use computers were already better paid before working with computers, therefore concluding that the technology-wage "premium" is primarily the result of workers with higher unobserved abilities being more likely to use advanced technologies.

In this paper we use a unique Linked Employee-Employer (LEE) data set containing longitudinal worker and plant information from 1985 to 1997 that allow us to estimate the effects of technology adoption, worker skill and the interaction of the two on the wages of individuals employed in manufacturing plants located in the State of Maryland. This is the first study of this kind conducted with longitudinal U.S. data that brings together both worker and firm information. We construct a wage model in line with work by Abowd, Kramarz & Margolis (1999), Goux & Maurin (1995), Entorf, Gollac and Kramarz (1995) and Lane, Miranda, Spletzer & Burgess (1998) to control for both observed and unobserved worker and firm heterogeneity, and include a direct measure of plant technology use to investigate the interaction between technology and skill. The longitudinal information on both workers and firms allows us to both control for the impact of unobserved characteristics on both dimensions, and also to shed some light on the view that wage differentials between skill and unskilled workers in the U.S. is correlated with technological change.

Three different data sets are linked to construct the analytical file: Maryland's Unemployment Insurance (UI) Records file, the Survey of Manufacturing Technology (SMT) and the Standard Statistical Establishment List (SSEL). The Unemployment Insurance Earnings Records contains quarterly earnings for all Maryland workers and is the source for constructed employer measures like employment, age and churning. We link this longitudinal data for each worker to Census administrative records to extract their demographic information like age, gender and race. A second link is made to the 1988 Survey of Manufacturing Technology which provides cross sectional information on technology use of 17 different technologies in manufacturing plants. A final link is made to the SSEL to obtain a measure of longitudinal sales for the employers.

Our data presents us with a challenge. On the one hand, we have longitudinal information on observable time-varying individual and firm characteristics. However, our primary variables of interest (i.e., technology and skill level) are cross-sectional in nature.[1] If we are to exploit the longitudinal dimension of the data to obtain unbiased estimates of observable individual and firm characteristics (e.g., tenure, experience, plant size, plant age), we would proceed by using a within estimator to control for unobserved individual and plant fixed effects. Note, however, that estimation of fixed effects also removes the effect of our observed but cross-sectional variables of interest, and therefore, we would not be able to ascertain their effect on individuals' wages. To get around this problem, we follow a modified version of Black and Lynch's (1998) two-step estimation procedure.

In the first step we exploit the longitudinal aspect of the data to estimate a wage

[1] For all but eight manufacturing plants that had a link to the 1993 SMT. This fact will be exploited later in the analysis.

equation employing a within individual-firm estimator to address omitted variable bias following Abowd *et al*. (1999). In the second step, we turn to a cross-sectional analysis to exploit this other aspect of the data. The time-varying coefficients from step 1 are used to compute an estimated residual --the pure worker-firm wage plus a statistical error-- that is then averaged over time to produce an estimate of the joint worker-plant fixed effect. This estimate is then regressed on our measure of plant technology, worker skill and the interaction of the two in order to determine the effect of these factors on the average pure worker-firm wage. Estimates from this type of cross-sectional analysis suffer from omitted variable bias resulting from worker and firm unobservable characteristics, and may change once these aspects are controlled (Entorf, Gollac & Kramarz (1999)). To see how this may be affecting our results, we supplement the analysis with results from a longitudinal analysis on a subset of plants for which we have longitudinal technology information.

From the cross-sectional analysis we find that plants with a higher number of technologies pay on average higher wages, that skilled workers earn higher wages than unskilled workers, and that the returns from a plant's technology use tend on average to accrue to the lower skill workers. These results are strikingly similar to results on french cross-sectional data by Entorf *et al*. (1999) as well as U.S. cross-sectional analysis in Doms *et al.* (1997) and Krueger (1993). Our longitudinal analysis, however, reveals that once we control for worker and firm unobservable characteristics, the interaction of skill with technology becomes not significant for high skilled workers, but unlike Entorf *et al*. (1999), is still significant and in fact reverses sign for low skilled workers. We find that low skilled

workers earn less in more technologically advanced plants. The combined results are taken as evidence of skilled biased technological change in U.S. manufacturing firms. We consider that this result — which could not be captured in the French data — is reflective of the higher flexibility of wages in the U.S. versus the relative wage rigidity of wages in France. The wage adjustment we find for low skilled workers in technology adopting plants is consistent with findings by Doms *et al*. (1995) that technology adoption is not correlated with skill upgrading. The results also indicate the presence of selection of workers when firms allocate technology in manufacturing plants. Selection however does not explain all the wage differentials we observe for unskilled workers across plants. The data suggest there are other stories at play in the economy. Groshen (91) provides a number of explanations for employer-based wage differentials while still maintaining a perfect competition model. These explanations range from unobserved characteristics of the workers and firms
(sorting models), unobserved characteristics of the firms where they work (compensating differentials), imperfect information models, agency models and insider wages. Another possibility that plays directly into the match technology-worker is Sattinger's model of an assignment economy. These results should be viewed with caution, however, given the small number of plants in the longitudinal sample.

If worker wages are affected by technology adoption then we would expect other worker outcomes to be affected. In particular does technology adoption affect worker mobility? This is the next question we tackle and for this we follow Topel and Ward's (1992) empirical mobility model. We employ Cox's proportional hazard model to estimate the probability of a worker exiting a plant as a function of our measure of plant technology, individual skill level, as well as worker wages and other observable individual and plant characteristics (e.g., gender, race, plant size). Our findings suggest that workers in more technologically advanced plants tend to be more mobile once we control for the effect of plant size. It also seems that high-skill workers have a higher probability of exiting the plant than their low-skill counterparts. However, not too surprisingly our technology-skill interaction indicates that high-skill workers employed in technologically advanced plants are less likely to exit, while we find the opposite for low-skill workers employed at these high-tech plants.

The paper is organized as follows. In the next section we describe the characteristics of this unique data set. Section III follows with a description of a model of wage determination that includes specific measures of technology and also the description of the two-step regression. Section IV presents the results from the two-step regression analysis, introduces our longitudinal analysis and contrasts the results from the two. In Section V, we present a model of mobility and section VI presents our mobility estimatio results. The last section summarizes our main conclusions.

II. DATA AND MEASUREMENT ISSUES

Given the uniqueness of the data set and the bearing it has on the type of analysis and estimation, we think it would be helpful to describe it at this point. Our longitudinal linked employer-employee data set is constructed from a variety of data sources. In particular

Census administrative records, Maryland's Unemployment Insurance Records, the Survey of Manufacturing Technology for 1988 and 1993, and the Standard Statistical Establishment List are used to construct the two analytical data sets employed in the analysis.

Demographic Characteristics Data

Demographic characteristics of individual workers are obtained from the Maryland Numident File, and the 1990 Decennial Census. The Numident File provides information on race, age and gender of all workers in the State of Maryland. We then used the Long Form of the Decennial Census to obtain the education on a substantial subset of the Maryland workforce and use it to create predicted education categories for the remaining workforce. Since this variable is clearly measured with error, we collapse educational attainment into high, low and medium predicted education. These categories roughly correspond to 1) high school dropouts, 2) high school graduates and those with some college, and finally 3) college graduates. We refer to these categories as high, low and medium skill workers.

Employer Characteristics Data

Firm and plant-level information comes from the Unemployment Insurance (UI) Wage Records of the State of Maryland, the 1988 Survey of Manufacturing Technology (SMT), and the 1985-1996 Standard Statistical Establishment List (SSEL). The UI Earnings Records is the source of the quarterly earnings measure we use in our analysis; forty-nine quarters worth of data covering the period between 1985:2 and 1997:2 were made available by the Jacob France Center at University of Baltimore.[2] Initially, UI covered only employers in the private non farm economy with eight or more employees. Over the years, however, the system has been continuously expanded and today it provides in essence the universe of employed workers. In the UI system, a variety of administrative data is maintained, but there are three important data sets which serve as the primary source of statistical uses. First, there is a master list of more than four million subject employers which contains the names and addresses of covered firms and both actuarial and statistical information. Secondly, information from the quarterly tax reports filed by employers is maintained. Finally, in all but 12 States, firms report the total wages paid to each employee during the quarter to determine an individual's eligibility and benefit amount when filing a UI claim.

It is this last data set and for the State of Maryland we use in our analysis. The file contains quarterly payments made by employers operating in Maryland to each of its employees during between 1985:2 and 1997:2, thus the usual caveats of miss-reporting and recall error that are typical of worker surveys do not apply. In addition to total quarterly earnings payments by the employer each record contains a Social Security Number (SSN) identifying the individual receiving the payments, the Employer Identification Number (EIN)

[2] Since 1997 the authors been members of a research team affiliated with The Jacob France Center at the University of Baltimore. The Center has maintained a data-sharing agreement with Maryland's Department of Labor, Licensing and Regulation since 1991. The Department requires the Center's researchers to honor state and federal laws and administrative regulations with respect to the confidentiality of the data made available.

identifying the employer making the payments and the year and quarter the record belongs to.[3] These identifiers serve as links to the other data sets. A recurring issue when working with administrative earnings data is that it does not contain information on the number of hours worked or weeks worked by the worker so computation of a wage rate is not possible. Some workers will earn high wages and work few hours which will be reflected in low quarterly earnings while some others will work many hours for the minimum wage which will result in average quarterly earnings.

In our analysis of wage changes and in order to limit the bias from unobserved labor supply effects, we restrict our sample following Topel & Ward (1992), and Lane *et al.* (1999) to include only "full quarter" jobs thus excluding quarters where the jobs begin or end. To further control for the number of hours and again following their work, we consider any quarter with earnings not reaching 70% of the minimum wage as non-employment.[4] Thus the wage analysis focuses on full quarter and full time jobs, and any job-quarter not meeting this threshold is considered an unemployment spell. From the UI Earnings Records we also construct quarterly plant level data, in particular plant employment, dummies for whether employment expanded or contracted by more than 20% from the previous quarter, and a measure of quarterly turnover over and above the establishment's employment expansion or

[3] A worker ID variable was created to replace the SSN immediately upon receiving the data. The additional security measure ensured that in fact we never worked with the actual worker SSN information. The Internal Revenue Service maintains the process for assigning EINs. An employer obtains an EIN by submitting IRS Form SS-4, Application for Employer Identification Number, to the IRS. Any business that pays wages to one or more employees is required to have an EIN as its taxpayer identifying number. There would be few, if any, employers that would not already have an EIN for taxpayer identifying purposes.

[4] This is computed as (0.7 x 40 x 4 x 4 x Minimum Wage).

contraction (churning as defined by Burgess, Lane & Stevens (forthcoming)). Again all these measures are based on full-quarter full-time jobs.

Sales at the firm level are obtained from the SSEL. This is the Census Bureau's sampling frame for businesses in all industries in the United States containing data such as firm sales, employment and geographic location. Our measure of labor productivity uses SSEL data from 1985-1996 and is constructed following Haltiwanger, Lane and Spletzer (1999), and Lane, Miranda, Spletzer & Burgess (1998). It is computed as the natural log of firm sales divided by employment. The sales to employment ratio should be regarded as a proxy for labor productivity since revenue is divided by employment rather than hours, and the GDP deflator is used rather than the appropriate firm specific price deflator.

Our technology measure comes from the 1988 Survey of Manufacturing Technology (SMT). This is the Bureau of the Census plant-based sample surveying approximately 10,000 manufacturing plants on the use of 17 separate technologies. These technologies include CAD/CAM, Computer Numerically Controlled Machines lasers and robots. (See Appendix B for a list and description of SMT technologies.) The industries covered are those included in major industry groups 34 - Fabricated Metal Products, 35 -Nonelectrical Machinery, 36 - Electric and Electronic Equipment, 37 - Transportation Equipment, and 38 - Instruments and Related Products. The data from the SMT allow us to construct a technology measure by identifying how many types of advanced manufacturing technologies a manufacturing plant utilizes and which. We construct our measure of technology in line with Doms, Dunne and Troske (1997) to be the number of technologies a plant uses, but distinct from other commonly used measures which are based on investment in computers and computer peripherals (e.g., Berman, Bound and Griliches (1994), Autor, Katz and Krueger (1996)). We will assume that plants that use a higher number of technologies are more technologically advanced.[5]

Having linked the different data sets the final analytical file consists of 547,665 quarterly records from 52 manufacturing plants in the state of Maryland employing a total of 35,628 workers. The structure of the individual data can be examined in Table 7 in Appendix A. The rows of this table correspond to the number of quarters a person is in the sample and the columns, with the exception of column (1a), correspond to the number of employers the individual had. An individual can only contribute to a single cell with the exception of column (1a) that represents the subset of workers from column (1) whose employing plant had at least one other individual with a previous employer in the sample. Tables 2 and 3 in Appendix A compares the plants and workers in our matched data set with the populations they are drawn from. Table 2 presents summary statistics for plants in our sample and for the total number of plants in the 1988 SMT. We can see that our plants are fairly representative of the total sample although they tend to use a slightly less number of technologies and are somewhat smaller. Table 3 presents summary statistic for all workers in Maryland employed in industry groups 34-38, and for the workers in our matched data set. We can see that the comparison between the two is remarkably similar in all fronts including

[5]This assumption is substantiated in Doms *et al*. (1997) where they show that technology counts is highly correlated to technological intensity.

mean quarterly earnings, skill level, age and other demographic characteristics.

III. MODEL: TWO-STEP WAGE EQUATION

We begin with a wage model that builds on work by Abowd *et al*. (1999) and Lane *et al*. (1999) and expand it to include a measure of technology adoption. Worker productivity is a function of observable characteristics like experience, tenure and education, but also of unobservable characteristics such as ability. Similarly firms have been shown to affect differently the wages of econometrically identical individuals depending on their observed and unobserved characteristics like size, age, technology use or managerial ability. The individual's wage is thus a function not only of his/her observed and unobserved characteristics, but also of the observed and unobserved characteristics of the plant she works at including technology. Taking from Abowd *et al*. (1999) notation, consider then the following wage equation:

$$w_{ijt} = \beta_1 x_{it} + \beta_2 p_{jt} + \theta_i + \psi_{j(i,t)} + \varepsilon_{ijt} \qquad \textbf{(1)}$$

where w_{ijt} is the logarithm of real quarterly earnings of worker $i=1,\ldots, N$ working at plant $j=1,\ldots, J$ during quarter $t=1,\ldots, T$; x_{it} is a vector of G time-varying exogenous observed worker characteristics of individual i, p_{jt} is the vector of F time-varying observed plant characteristics, θ_i is the pure worker effect, $\psi_{j(i,t)}$ is the pure plant effect for the plant at which worker i is employed at date t (denoted $j(i,t)$) and ε_{ijt} is the statistical residual.

Further consider the following decompositions of the pure worker effect into an observed component and an unobserved one so that

$$\theta_i = \alpha_i + \eta u_i \tag{2}$$

where α_i is the unobserved person-specific intercept, u_i is a vector of observed time-invariant individual characteristics (e.g., gender, race and skill level), and η is the vector of coefficients. Similarly consider a decomposition of the pure plant effect into an observable component and an unobservable one so that

$$\psi_j = \phi_j + \gamma R_j \tag{3}$$

where ϕ_j is the firm-specific intercept, R_j denotes observed technology use in plant j (or rather the fixed component associated with it) and γ is the technology coefficient.

Abowd *et al.* (1999) have shown that failure to control for both worker and firm unobserved heterogeneity results in biased estimates of β_1 and β_2, the coefficients of the observable time-varying worker and plant characteristics in equation (1). We then use a within-individual-firm estimator to control for both worker and plant fixed effects and deal with the potential correlation between one of our regressors and worker-specific and plant-specific time-invariant components of the error term.[6] Note, however, that estimation of fixed effects also removes the effect of our observed but time-invariant variables of interest, technology use and skill level (remember technology comes from a cross-sectional data set)

[6]See Abowd *et al* (1999).

and therefore, we would not be able to ascertain their effects on individuals' wages.

In order to distinguish the effect of technology on wages from the pure plant effects, we adopt a modified version of Black and Lynch's (1998) two-step estimation procedure. Step 1 involves estimating equation (1) with fixed effects to get unbiased estimates of $\$_1$ and $\$_2$. The time-varying regressors include, for the individual, age of worker and current job tenure, and plant age, plant size, churning and employment expansion and contraction for the plant. Tenure is actual tenure constructed from the data and is, thus, left censored. Our regression also include year dummies to control for any time trend.

Having estimated model (1), we then generate predicted values of the pure worker and plant effects by taking the residuals which contain the portion of real wages that could not be explained by our estimates of the time-varying worker and plant characteristics *(b_1 and b_2)* as well as time dummies:

$$w_{ijt} \ \& \ b_1 x_{it} \ \& \ b_2 p_{jt} \ ' \ 2_i \ \% \ R_j \ \% \ g_{ijt} \qquad \textbf{(4)}$$

or substituting (2) and (3) for 2_i and R_j :

$$w_{ijt} \ \& \ b_1 x_{it} \ \& \ b_2 p_{jt} \ ' \ "_i \ \% \ u_i 0 \ \% \ N_j \ \% \ (R_j \ \% \ g_{ijt} \ ' \ w|_{xp} \qquad \textbf{(5)}$$

We then average this value over the 1985-1997 period and for each worker-firm pairing to get an estimate of the joint worker-plant time invariant component of the residual:

$$E_{ijt}[w|_{xt}] \ ' \ u_i 0 \ \% \ (R_j \ \% \ n SR_{[ij]} \qquad \textbf{(6)}$$

In the second step of our estimation, we regress the averaged residuals on individuals' skill level and other demographic characteristics, u_i, the level of technology used in the plant where the individual works, R_j, and the interaction of the skill level and technology use, SR_{ij}, to get estimates of *0*, *(* and *n*.

IV. REGRESSION RESULTS

Results from the within worker-firm wage regression are presented in Table 4. Coefficients on the time varying worker characteristics are in line with standard human capital regression results and indicate that an individual's experience --as proxied by age-- and also tenure increase earnings at a decreasing rate. More interesting and in line with results in Lane *et al*. (1999) are the estimated effects of time-varying firm characteristics. We find that after controlling for worker-firm fixed effects older plants pay less, larger firms pay relatively more, expanding firms also pay significantly more, contracting firms less and finally that increases in firm productivity lead to increases in earnings. We also find that plants with higher churning have to pay more for the same workers. Focusing now on our variables of interest —technology and skill— Table 5 presents the results from the cross-sectional analysis on the estimated pure worker-firm effect. Our results indicate that workers employed in plants that have adopted a higher number of technologies are payed more and also that high skilled workers are payed more than either medium or low skilled workers. These results are consistent with the results obtained by Krueger (1993), Autor, Katz and Krueger (1996), Doms, Dunne and Troske (1997) and Entorf, Gollac and Kramarz (1997), all of whom show that technology use is associated with higher worker wages even after controlling for observable worker characteristics.   As expected, we also find that higher skilled workers earn higher wages compared to their lower skilled counterparts. However, the coefficient of the interaction between skill and technology indicates that on average the wage premium associated with more technologically advanced plants tends to go to lower skilled workers. This result is surprisingly similar to findings by Entorf *et al.* (1997) on a cross-sectional analysis of French data where they find that the wage premium related with computer use gets apportioned to low-education workers.[7]

We know, however, that results from this type of cross-sectional analysis suffer from omitted variable bias from worker and firm unobservable characteristics and have in fact been shown to change quite considerably once these aspects are controlled (Entorf, Gollac & Kramarz 1999). To see how this may be affecting our results, we supplement the analysis with results from a longitudinal analysis on a restricted sample of plants for which we were able to construct longitudinal technology information from the SMT. Only eight such plants could be identified due to the fact that the 1988 and 1993 SMTs are not designed to be a panel.

Our longitudinal technology sample contains a total of 118,191 quarterly records that correspond to the 7,421 individuals who worked in those eight manufacturing plants at some

[7] We rerun the cross-section analysis on the average obtained from earnings in and around 1988 since this is the SMT year we used to extract the technology information. We know the number of technologies did change for these plants between the 1985 to 1997 so by restricting the number of years to the survey year and around we attempt to increase the precision of our technology measure. We find the results don't change significantly.

point between 1985 and 1997. The plants in this sample have a 1988-1993 average employment of 350 workers, which is right between the mean employment figures of the 1988 SMT and our SMT-UI sample (see Table 2). Their mean number of technologies in the 1988-1993 period is 3 ranging from 0 to 9 technologies per plant. Regarding worker statistics, this sample holds a smaller proportion of whites (66% compared to our previous 80%) and a slightly higher proportion of low skilled workers (25% compared to the 19.2% in the Maryland UI with SICs 34-38). The proportion of high skill workers, though, is preserved at around 5.5%. Finally, the mean quarterly wage is $6,814 which is below the approximately $8,000 in the Maryland UI (see Table 3).

The model we estimate is the same one we used in the first step of our two-step regression (equation (1)), but now it includes a time-variant measure of technology as well as the interaction of skill and technology. Results from this longitudinal regression are presented in Table 6. They show that once we control for worker and firm fixed effects the effect of the interaction term for high skill workers becomes not significant while the interaction with low skill workers is now negative and still significant. It would appear there is some selection of workers to technology. Workers are assigned to new technologies according to unobserved abilities so that not only does the premium disappear once we control for the unobservable for high skill workers but it actually becomes negative for low skill workers. The now negative effect on the interaction between low skill workers and technology is also suggestive of direct evidence of skill biased technical change in US manufacturing firms.

This result is not inconsistent with findings by Doms *et al*. (1997) who find no correlation between skill upgrading and technology use. The adjustment to changing demand conditions can come through wages or through employment. In a wage flexible economy one would expect low skill workers facing changing demand conditions to see their wages adjust and in fact fall in technology adopting plants rather than see their jobs lost. This is in contrast with results on French data by Entorf *et al*. (1999) who find the impact of technology on low education workers disappears after controlling for worker unobservable. They argue this is consistent with wages being rigid in France, and with changes in demand conditions being adjusted through employment changes. The U.S. economy, however, is much more dynamic, and shifts in demand are likely absorbed through wage changes.

V. A MODEL OF MOBILITY

New production processes seem to be working to reduce demand for less skilled workers. Some evidence for this was found in the previous section. But wage adjustment may not be the only mechanism restoring the equilibrium, in fact we might expect to see increased mobility for those workers whose wages are being affected by technology adoption whenever the new wage falls below their reservation wage. In this section we investigate how technology adoption impacts the mobility of the worker employed in manufacturing plants located in the State of Maryland beyond the effect it has via the wage mechanism. To investigate this issue we next construct an empirical model of mobility decisions that builds on that of Topel & Ward (1992) to look at the impact technology adoption and other firm characteristics have on the probability of separation of the worker. This section specifically investigates the role played by the firm in the mobility rate of the worker. Does technology adoption or failure to adopt have an impact on the hazard rate of workers employed by the plant?

The individual seeks to maximize her wealth. As such she makes her mobility decision by comparing the expected present value of the current job with the expected present value of the alternative (be it another job or unemployment). In our model the expected present value is a function of the standard covariates in the literature, the wage rate (w), experience (X) and tenure (T). But firms are not homogeneous entities; for example, they may have different production technologies, hiring and training costs, turnover/retention or training policies even within narrowly defined industry groups. These differences may result in different optimal wage growth paths across firms, and thus provide information beyond that conveyed by the current wage, experience or tenure on their own.[8] If this is the case then observed earnings, experience and tenure are not a sufficient triplet to describe the value of a job or to make between-job comparisons for mobility decisions.[9] We extend a standard mobility model to include specific firm characteristics. This has the effect of relaxing the assumption that expected earnings growth is the same across jobs. In addition to our key technology measure, we also include the age and size of the plant, its employment churning rate, a quarterly dummy indicating whether the plant's employment increases or decreases by more

[8]Topel &Ward (1992) only include firm size as a control and motivate their inclusion after the fact based on internal career markets.

[9] This insight comes from Topel (1986).

than twenty percent, 2-digit SIC industry dummies, season dummies, and whether or not it is part of a multi-establishment firm. For this model we adopt a proportional hazard specification such that:

$$\lambda(w,t,x,p,\beta_1,\beta_2,\lambda_0) = \lambda_0(t)\exp(w\beta_0 + x'\beta_1 + p'\beta_2) \qquad \textbf{(7)}$$

where λ_0 is a baseline hazard, w is a real wage function, x is a vector of observable worker characteristics, p is a vector of firm observable characteristics that includes technology and the β*s* are the coefficients of interest. The effect of explanatory variables in this specification is to multiply the baseline hazard λ_0 by a factor which does not depend on duration t. Cox's (1972) partial likelihood approach can be used to estimate the β*s* without specifying the form of the baseline hazard function λ_0. The benefit of this approach is that we avoid imposing structure on the data.

VI. MOBILITY ESTIMATION RESULTS

We start by estimating the empirical hazard rate for workers by the level of technology adopted by their employer, and the gender and skill level of the worker. For this, plants are classified as 'high', 'medium' and 'low', and employees are classified as 'high-skill' or 'skilled', 'medium-skill' and 'low-skill' or 'unskilled' workers. Table 8 and Figure 1 present results from estimating those empirical hazards. We find that the fewer the number of technologies adopted by the plant the higher the hazard of exiting that plant, and also that lower skilled workers have a higher hazard of exiting. However, these results are only descriptive in nature and do not control for key mobility variables like earnings and experience.

Table 9 reports parameter estimates for various forms of the hazard function in [7]. The specifications contain the usual worker heterogeneity controls like gender, race, education and age (which acts as a proxy for experience) and an age-tenure interaction. Plant variables include the number of technologies in use at the plant in 1988, the size and age of the plant, the churning rate, dummies for whether the plant's employment expanded or contracted by 20% relative to the previous quarter, a dummy for whether the plant belongs to a multi-unit firm and also industry dummies. In addition, we include calendar quarter shifters. The specifications in columns (1) through (4) do not include current wage as a control variable while the rest of them do.

The specification in column (1) omits the wage as well as the less common firm characteristics and technology. This specification serves as a reference point to which to compare results from other specifications. Column (1) shows that as workers age (and gain experience) their hazard rate falls. The point estimate shows that every additional year reduces the probability of exit of the worker by one percentage point. Females have an 8.8% higher hazard rate of exiting the manufacturing plants than males and non-whites have between 15 and 20% higher rate of exiting than whites. Not surprisingly, we also find that unskilled workers employed at these manufacturing plants have a 27% higher rate of exit relative to the reference group of medium skilled workers. Skilled workers fare statistically no different from this reference group. Finally, we also find that the larger the size of the plant the lower is the probability of exit and that workers employed for multi-unit plants have a higher probability of exiting the observed plant. Other controls include the industry at the two digit level and the quarter shifters. These results are all comparable to Topel & Ward (1992).

We then move on to column (2) where in addition to the widely used size of firm and industry controls, we also include less commonly used plant characteristics such as churning rate, the age of the plant, and dummies for the plant's employment expansion and contraction. Notice, though, we are not yet including our technology measure. The coefficients were all found to be strong and significant which is a clear indication that these type of plant characteristics are important in determining worker mobility. For example, not surprisingly we find that an increase of one percent in the churning rate increases the probability of exit by .47%. We also find that working for an expanding plant lowers the probability of exit to 61% of that of workers employed in more stable plants, and that working for a contracting plant more than doubles the probability of exit relative to the same group.[10] The age of the plant also has a positive effect on the hazard. The estimates indicate that for every additional year the plant has been in operation the probability of worker exit increases 1.1%. Also worth noticing is that, compared to column (1), the size of plant effect loses 25% of its impact. This result seems to indicate that plant size was in fact partially capturing the effects of the plant's churning rate and employment expansion and contraction.

[10] Expanding is defined as an increase in full-quarter employment of 20% or more relative to the previous period. Contract is defined as a reduction in full-quarter employment of 20% or more relative to the previous period.

In specifications (3) and (4), we introduce technology and also explore the hypothesis that a plant's technology is correlated with other plant characteristics such as size.[11] Column (3) shows the results when we include technology and our technology-skill interaction, but exclude the size variable. In column (4) we again include plant size along with our technology variable. This way, we will be able to see how the coefficients of the technology and size variables vary if at all.

Interestingly, our comparison of columns (3) and (4) suggest that technology and size are indeed correlated. If we were to just look at the results in column (3), we would conclude that workers in plants that use more technologies have a lower probability of exit. However, when we also control for plant size as well as technology (column (4)), we realize that workers in technologically intensive plants seem to have a higher probability of exit. The reason for these seemingly contradictory results is that it is highly likely that plant size and technology use are correlated. Size has a negative effect on the probability of exit while technology seems to have a postive effect. When we include size, but omit technology (column (2)), the size variable picks up the positive effect of technology use thus losing approximately 26% of its estimated impact effect (as compared to column (4).) Analogously, when we include technology but omit size, our technology variable picks up the negative effect of size, thus becoming (slightly) negative. Thus, as we control for both technology and plant size, as well as other worker and plant characteristics (column (4)), the results suggest that

[11]For instance, Troske (1997) finds that the size of the plant and capital intensity are positively correlated.

worker mobility is higher in plants where more technology is used while size makes them less likely to exit.

Given that this is the first empirical analysis of job mobility that uses this type of technology measure, the interpretation of this result is not quite obvious. It could indicate that working for high-tech plants may be a signal of unobserved worker characteristics; that is, if in line with the conclusions of Doms *et al.* (1997), Entorf *et al.* (1999), we assume that workers with higher (unobserved) ability are more likely to work at high-tech plants, then it can be argued that these workers are more likely to receive better outside job offers (i.e., their opportunity wage is higher), and thus, are more mobile and more likely to exit the plant.[12] But it could also indicate that the new production processes require higher quality job matches and that low quality matches are dissolved earlier.

Turning our attention to the interaction between skill and technology, we find that, relative to medium-skill workers, unskilled workers are more likely to exit the firm the larger the number of technologies adopted by the plant. This might again may be an indication of skill biased technical change working through employment effects. The effect on the interaction is only marginally significant for skilled workers and works by reducing the risk of exit for this group. As expected, the inclusion of the technology interaction with skill also affects the skill coefficients. Before the inclusion, only unskilled workers had a significantly higher risk of exiting the plant relative to medium-skill workers. However, with the addition of

[12]This line of argument presumes that in a majority of cases, exiting the plant is a voluntary act. Our data, however, does not allow us to discern what workers are fired and which ones exit the plant voluntarily.

the interactive term, both skilled and unskilled workers now have a significantly higher risk of exiting, roughly 13 and 11% respectively.

Column (5) conditions on the log quarterly wage from the current period. Like Topel & Ward (1992), we also find that the job-specific wage is a key determinant of mobility. We find that a 10% within-career wage increase reduces the probability of leaving the job by about 9 percentage points — which is a significantly stronger impact than the 2% they obtained. Also worth noticing is that even after we control for wages, the effects of our technology and technology-skill interaction variables do not vary significantly. Thus, the hypothesis presented in relation to our column (4) results is maintained.

However, conditioning on the wage affects other estimates, and just in the way that we expect based on previous empirical studies. For example, in column (1) we found that females and non-whites had a significantly higher hazard of exit, but once we control for wages, we find that females' probability of exiting is in fact 80% that of males with similar characteristics, and that blacks have a probability of exiting that is 92.3% that of whites. These results can be an indication that these populations are faced with outside offers that are of lesser value relative to white men but it could also indicate they have a stronger preference for a stable job. The coefficient on other non-whites is now not significant.

We also see that the skill coefficient jumps from a 13% higher risk to a much higher 32% probability of exiting the plant relative to medium-skilled workers. This suggests that high skilled workers are paid to prevent their "jumping" from the plant. On the other hand, once we control for wages the hazard of exit of unskilled workers relative to medium skilled workers is not significantly different which may be indicating they are getting a wage signal to leave the plant.[13] Again this result would be indicative of skilled biased technical change. It is also worth noticing that once the wage is included that the point estimate although insignificant is now negative.

V. CONCLUSIONS

Making use of a unique linked data set we have found direct evidence of skill biased technological change in US manufacturing plants. While the analysis is restricted to plants located in the State of Maryland, our analysis is consistent with other findings in the U.S. and with similar data in France. We have shown that there is a considerable selection of workers to manufacturing technologies by ability so that once we control for the unobservable, the premium associated with working with these technologies disappears for high education workers. However, the effect of working with technology for low education workers reverses sign and actually becomes negative. What in cross-sectional analysis appeared to be a premium accruing to low skilled workers employed in technologically advanced plants, in fact turned out to be a result of selection. In fact, low education workers were found to suffer a wage penalty in high technology plants. This finding is in stark contrast with similar analysis conducted with French data where they find the cross-section "premium" completely disappears once they control for unobservable individual characteristics. However, it is

[13] We run an additional hazard where we include our productivity measure. Our results suggest that workers at more productive plants have a lower probability of exiting. Its inclusion does not qualitatively affect any of the previous results, although it increases the technology and the plant size coefficients.

argued that this is due to the different workings of the French and the U.S. economy. While the French economy, one of rigid wages, adjusts to changes in relative labor demand through changes in employment, the more dynamic U.S. economy adjusts through wage changes. This wage adjustment is reflected in the technology adopting plants that we were able to identify in the U.S. manufacturing sector. The richness of the SMT data as regards to the type of technology was not fully exploited for this paper. Some of the technologies are clearly used by highly educated workers while others are used by less educated workers. In the future we plan to investigate this aspect of the data to see how different technology types may be affecting the different types of workers.

Regarding our analysis of the role of technology adoption of worker mobility, we have found that firm characteristics like size, age, churning and the number of technologies do significantly affect the probability of exit of the worker even after controlling for earnings. This indicates that wages do not fully capture the information weighed by the worker when making their mobility decision. In a larger sense, this is consistent with findings that firms are not homogeneous entities even within narrowly defined industry groups. Our findings seem to indicate that skill biased technical change acts not only through wages, but also that the adjustment takes place via the employment mechanism. While unskilled workers are generally less mobile than either their high or medium-skill counterparts, their probability of exit increases with the number of technologies adopted. It would appear that less skilled workers are being pushed to less technologically advanced plants.

We also find that the larger the number of technologies adopted by the plant the higher is the probability of exit of the worker. We attribute this to the view — which is consistent with Entorf, Gollac and Kramarz, and Doms, Dunne and Troske — that workers who we observe employed at technologically advanced plants tend to have higher unobserved ability, and therefore, command a higher opportunity wage which makes them more likely to exit.

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APPENDIX A: Tables and Regression Results

Table 1: Variable Definition

Plant - Quarter Level Variables:

Employment Expansion Dummy =	1 if quarterly employment increases by more than 20% from previous quarter
Employment Contraction Dummy =	1 if quarterly employment decreases by more than 20% from previous quarter
Churning =	[worker flow - abs(job flow)] / average employment, where worker flow = hires + exits job flow = hires - exits average employment = (current employment + previous employment)/2

Firm - Year Level Variable:

Firm Productivity Measure =	Log(Deflated Firm Annual Sales / Firm Annual Employment)

Individual Level Variable:

Low Skill:	High school dropout
Medium Skill:	High school graduate and some college
High Skill:	College graduates

Table 2: Sample Statistics for Plants

	1988 SMT	1988 SMT - MD UI Match
	(1)	(2)
Mean Employment	362.5	335.1
Size Class:		
1-99	45.1%	46.2%
100-499	37.7%	40.4%
500+	17.2%	13.5%
Age:		
0-4	11.4%	15.4%
5-15	31.6%	26.9%
16-30	29.8%	34.6%
30+	27.2%	23.1%
Mean Number of Technologies	3.8	3.3
Technology Classes:		
0-3	55.7%	63.4%
4-6	23.5%	25.0%
7-9	12.6%	3.8%
10+	8.3%	7.6%
Industry:		
Fabricated Metal	23.4%	32.7%
Machinery Equipment	27.3%	23.1%
Electrical Equipment	22.8%	19.2%
Transportation Equipment	13.1%	13.5%
Instruments	13.4%	11.5%
N	9,378	52

Table 3: Summary Statistics for Workers

	UI MD	1988 SMT - MD UI Match
	(1)	(2)
Mean Age	39.79	40.15
Percent Female	28.09%	26.40%
Percent White	80.13%	79.50%
Percent Black	13.38%	14.80%
Skill Level		
Low	19.19%	21.00%
Medium	75.22%	73.40%
High	5.59%	5.60%
Mean Quarterly Wage	8,285.52	8,339.90
N	201,700	35,628

APPENDIX A (continued)

Table 4: Wage Regression (Step 1)
Worker and Plant Fixed Effects Absorbed
Dependent variable: Log of real wages

Variable	(1)	(2)
Worker Age 25-54	0.072	0.076
	(0.0023)	(0.003)
Worker Age 55-65	0.056	0.055
	(0.0029)	(0.003)
Tenure	0.013	0.016
	(0.0002)	(0.0002)
Tenure squared	-0.0002	-0.0002
	(0.000003)	(0.000004)
Firm Age 2-10	-0.032	-0.0418
	(0.0037)	(0.004)
Firm Age 10+	-0.117	-0.1009
	(0.0042)	(0.005)
Churning	0.052	0.0387
	(0.0047)	(0.005)
Log of Quarterly Employment	0.091	0.0911
	(0.0013)	(0.001)
Employment Expansion	0.026	0.0348
	(0.0015)	(0.002)
Employment Contraction	-0.002	-0.0056
	(0.0022)	(0.002)
Firm Productivity Measure	-	0.0292
		(0.0007)
Year Dummies	Yes	Yes
N	525,658	440,405
R - squared	0.8605	0.865
Standard Errors in parenthesis		

APPENDIX A (continued)

Table 5: Wage Regressions (Step 2)
Cross-Section Regression
Dependent variable: pure worker-firm effect (see equation [6])

Variable	No Productivity Measure in Step 1 (1)	Productivity Measure in Step 1 (2)
Constant	8.1608	8.0115
	(0.0029)	(0.0032)
High Skill	0.2107	0.2212
	(0.0042)	(0.0046)
Low Skill	-0.1568	-0.1512
	(0.0025)	(0.0028)
High Skill*Technology	-0.0083	-0.0089
	(0.0005)	(0.0006)
Low Skill*Technology	0.0070	0.0067
	(0.0004)	(0.0004)
Male	0.3858	0.3766
	(0.0012)	(0.0013)
Other race	-0.2001	-0.2031
	(0.0030)	(0.0033)
Black	-0.2669	-0.2656
	(0.0016)	(0.0017)
Technology	0.0069	0.0014
	(0.0002)	(0.0002)
Multi-Unit Dummy	0.0475	0.0352
	(0.0017)	(0.0018)
Industry Dummies	Yes	Yes
N	35,544	34,006
R - squared	0.272	0.2615

(Standard errors in parenthesis)

APPENDIX A (continued)

Table 6: Longitudinal Analysis
Worker and Plant Fixed Effects Absorbed
Dependent variable: Log of Real Wages

Variable	(1)	(2)
Worker Age 25-54	0.0834	0.0869
	(0.0058)	(0.0059)
Worker Age 55-55+	0.0393	0.0438
	(0.0073)	(0.0074)
Tenure	0.0235	0.0235
	(0.0006)	(0.0006)
Tenure squared	-0.0001	-0.0001
	(0.00001)	(0.000008)
Log of Firm Age	-0.1129	-0.1056
	(0.0083)	(0.0087)
Churning	0.2481	0.2508
	(0.0141)	(0.0141)
Log of Quarterly Employment	0.1774	0.1780
	(0.0031)	(0.0032)
Employment Expansion	0.0780	0.0778
	(0.0033)	(0.0033)
Employment Contraction	-0.0224	-0.0221
	(0.0040)	(0.0040)
High Skill*Technology	-	-0.0013
		(0.0019)
Low Skill*Technology	-	-0.0056
		(0.0015)
Number of Technologies	-	0.0028
		(0.0009)
Year Dummies	Yes	Yes
N	114,949	114,949
R - squared	0.81845	0.81849

(Standard errors in parenthesis)

Table 7
Structure of the Individual Data by Quarters in Sample and Number of Employers

Quarters in Sample	Number of Employers 1	1a	2	3	Total
1	3508	2879	0	0	3508
2	2446	2088	15	0	2461
3	2002	1657	18	1	2021
4	1568	1363	27	0	1595
5	1398	1208	12	0	1410
6	1330	1137	25	0	1355
7	1363	1209	16	1	1380
8	1269	1107	14	0	1283
9	1099	962	34	1	1134
10	1114	994	18	1	1133
11	1085	800	17	0	1102
12	844	738	17	2	863
13	836	749	24	0	860
14	755	675	18	1	774
15	746	663	10	0	756
16	756	683	11	1	768
17	724	668	12	0	736
18	854	779	20	0	874
19	683	622	14	1	698
20	451	399	17	0	468
21	470	421	19	1	490
22	525	469	16	0	541
23	441	400	14	1	456
24	575	475	8	1	584
25	401	367	14	0	415
26	404	373	9	0	413
27	332	305	7	0	339
28	440	401	10	1	451
29	430	406	6	0	436
30	260	209	15	0	275
31	330	302	8	0	338
32	290	260	5	1	296
33	281	240	7	0	288
34	283	255	10	0	293
35	355	327	6	0	361
36	360	322	2	1	363
37	367	344	5	0	372
38	610	557	15	0	625
39	148	111	6	0	154
40	158	141	3	0	161
41	228	200	6	0	234
42	199	178	4	0	203
43	341	327	4	0	345
44	571	489	4	0	575
45	104	78	2	0	106
46	184	144	2	0	186
47	1147	971	2	0	1149
Total	35065	30452	548	15	35628
Percentage	98.4%	85.5%%	1.5%	0.0%	100.0%

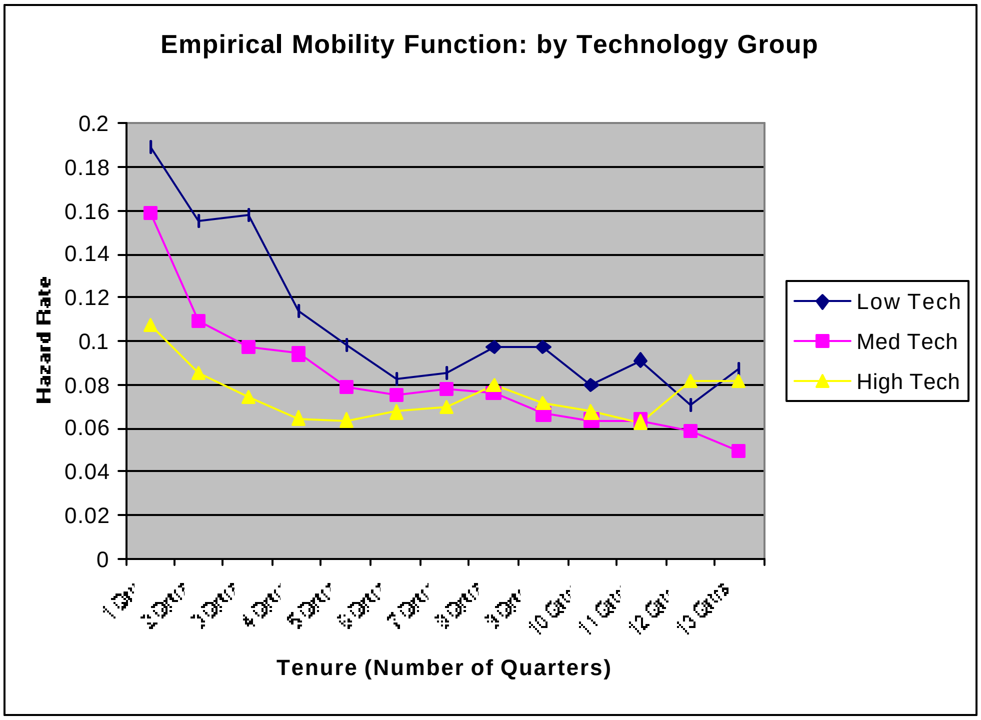
Column 1a refers to the subset of individuals with only one employer whose employing plant had at least one other individual who had changed firms at least once during the observed period.

Table 8: Empirical Mobility Functions by Technology Class, Gender & Skill

	Current Job Tenure (Quarters)												
	1	2	3	4	5	6	7	8	9	10	11	12	13
Technology Class													
Low Tech	0.19	0.16	0.16	0.11	0.10	0.08	0.09	0.10	0.10	0.08	0.09	0.07	0.09
Medium Tech	0.16	0.11	0.10	0.09	0.08	0.08	0.08	0.08	0.07	0.06	0.06	0.06	0.05
High Tech	0.11	0.09	0.07	0.06	0.06	0.07	0.07	0.08	0.07	0.07	0.06	0.08	0.08
Technology Class & Male													
Low Tech	0.18	0.16	0.16	0.13	0.10	0.08	0.09	0.10	0.08	0.07	0.08	0.06	0.09
Medium Tech	0.16	0.12	0.10	0.10	0.08	0.07	0.07	0.08	0.06	0.07	0.06	0.05	0.05
High Tech	0.11	0.08	0.07	0.06	0.06	0.07	0.07	0.08	0.08	0.07	0.07	0.08	0.08
Technology Class & Female													
Low Tech	0.20	0.15	0.16	0.09	0.10	0.09	0.08	0.09	0.13	0.10	0.11	0.08	0.09
Medium Tech	0.15	0.09	0.09	0.08	0.07	0.08	0.10	0.07	0.08	0.06	0.07	0.08	0.05
High Tech	0.10	0.09	0.08	0.06	0.07	0.07	0.06	0.09	0.06	0.06	0.05	0.08	0.08
Technology & Skill													
Low Tech Unskilled	0.23	0.19	0.21	0.13	0.15	0.08	0.09	0.10	0.12	0.06	0.06	0.09	0.05
Low Tech Skilled	0.14	0.14	0.11	0.10	0.08	0.10	0.13	0.13	0.10	0.08	0.12	0.17	0.21
Med. Tech Unskilled	0.18	0.13	0.10	0.10	0.08	0.07	0.08	0.07	0.06	0.07	0.06	0.05	0.05
Med. Tech Skilled	0.12	0.07	0.07	0.08	0.07	0.06	0.09	0.06	0.04	0.08	0.03	0.06	0.04
High Tech Unskilled	0.15	0.12	0.10	0.08	0.08	0.08	0.08	0.09	0.10	0.09	0.06	0.10	0.08
High Tech Skilled	0.08	0.06	0.07	0.06	0.06	0.06	0.07	0.07	0.06	0.07	0.08	0.10	0.10
Technology & Skill & Male													
Low Tech Unskilled	0.23	0.21	0.21	0.15	0.15	0.07	0.08	0.10	0.13	0.06	0.05	0.09	0.04
Low Tech Skilled	0.13	0.12	0.13	0.10	0.06	0.12	0.14	0.16	0.13	0.07	0.12	0.13	
Med. Tech Unskilled	0.18	0.14	0.10	0.11	0.09	0.07	0.06	0.06	0.06	0.07	0.06	0.05	0.05
Med. Tech Skilled	0.11	0.06	0.08	0.07	0.08	0.06	0.08	0.05	0.03	0.08	0.03	0.04	0.03
High Tech Unskilled	0.16	0.12	0.10	0.08	0.07	0.09	0.08	0.08	0.11	0.10	0.08	0.10	0.09
High Tech Skilled	0.08	0.06	0.07	0.06	0.06	0.06	0.07	0.06	0.06	0.06	0.07	0.09	0.10

All sets of Mobility functions are statistically different under the Log-Rank, Wilcoxon and LR tests.

Figure 1



Empirical Mobility Function: by Technology Group
Hazard Rate
0.2
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
Low Tech
Med Tech
High Tech
Tenure (Number of Quarters)

Table 9: Cox Proportional Hazard: Coefficients (* are Time-Varying)

	(1)	(2)	(3)	(4)	(5)
Current Wage*	-	-	-	-	-0.907
					(0.0147)
Female	0.085	0.073	0.080	0.073	-0.220
	(0.0134)	(0.0138)	(0.0138)	(0.0138)	(0.0145)
Black	0.143	0.118	0.129	0.116	-0.080
	(0.0165)	(0.0170)	(0.0170)	(0.0170)	(0.0173)
Other Race	0.180	0.121	0.098	0.133	-0.049
	(0.0343)	(0.0354)	(0.0354)	(0.0354)	(0.0358)
Race Not Reported	-0.006	-0.031	-0.036	-0.032	0.014
	(0.0401)	(0.0414)	(0.0414)	(0.0414)	(0.0414)
Skilled	0.037	0.035	0.125	0.120	0.281
	(0.0256)	(0.0262)	(0.0486)	(0.0486)	(0.0481)
Unskilled	0.227	0.219	0.105	0.106	-0.029
	(0.0146)	(0.0150)	(0.0263)	(0.0264)	(0.0264)
Log Worker Age*	-0.017	-0.014	-0.015	-0.015	-0.004
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Age-Tenurre Interaction	0.001	0.001	0.001	0.001	0.000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Log Age Firm*	-	0.018	0.015	0.018	0.025
		(0.0008)	(0.0008)	(0.0008)	(0.0008)
Log Size Firm*	-0.195	-0.146	-	-0.198	-0.147
	(0.0062)	(0.0072)		(0.0088)	(0.0090)
Log Churn*	-	0.477	0.500	0.505	0.494
		(0.0090)	(0.0096)	(0.0094)	(0.0095)
Expand 20%>*	-	-0.102	-0.110	-0.121	-0.060
		(0.0262)	(0.0263)	(0.0263)	(0.0263)
Contract 20%>*	-	1.078	1.186	1.073	1.073
		(0.0303)	(0.0300)	(0.0303)	(0.0303)
Number of Technologies	-	-	-0.012	0.023	0.029
			(0.0023)	(0.0028)	(0.0029)
Technology-Skilled Interaction	-	-	-0.014	-0.014	-0.014
			(0.0066)	(0.0066)	(0.0065)
Technology-Unskilled Interaction	-	-	0.024	0.023	0.024
			(0.0041)	(0.0041)	(0.0041)
Multi-Unit	0.216	0.285	0.075	0.337	0.430
	(0.0219)	(0.0232)	(0.0209)	(0.0238)	(0.0238)
SIC35	0.233	0.182	0.053	0.163	0.072
	(0.0237)	(0.0246)	(0.0243)	(0.0248)	(0.0248)
SIC36	0.030	0.173	0.084	0.136	0.139
	(0.0241)	(0.0258)	(0.0258)	(0.0261)	(0.0263)
SIC37	0.322	0.284	-0.018	0.335	0.335
	(0.0245)	(0.0265)	(0.0221)	(0.0270)	(0.0270)
SIC38	0.211	0.306	0.205	0.170	0.324
	(0.0268)	(0.0282)	(0.0313)	(0.0316)	(0.0322)
Winter	-1.099	-0.902	-0.896	-0.909	-0.911
	(0.0172)	(0.0181)	(0.0182)	(0.0182)	(0.0181)
Spring	0.004	0.134	0.140	0.140	0.106
	(0.0162)	(0.0170)	(0.0170)	(0.0170)	(0.0170)
Fall	0.077	0.166	0.202	0.157	0.151
	(0.0165)	(0.0173)	(0.0172)	(0.0173)	(0.0172)

Observations	36,184	36,,84	36,184	36,184	36,184
-2 log likelihood	576,549.65	535,685.9	536,026.1	535,546.6	531,831.1

(Standard Errors in Parentheses)

Table 10: Cox Proportional Hazard: Hazard Ratios (* are Time-Varying)

	(1)	(2)	(3)	(4)	(5)
Current Wage*	-	-	-	-	0.404
Female	1.089	1.076	1.075	1.083	0.802
Black	1.153	1.125	1.124	1.138	0.923
Other Race	1.198	1.129	1.143	1.103	0.953
Race Not Reported	0.994	0.970	0.969	0.964	1.014
Skilled	1.038	1.036	1.128	1.133	1.324
Unskilled	1.256	1.245	1.112	1.111	0.971
Log Worker Age*	0.983	0.986	0.985	0.985	0.996
Age-Tenurre Interaction	1.001	1.001	1.001	1.001	1.000
Log Age Firm*	-	1.018	1.018	1.015	1.025
Log Size Firm*	0.824	0.865	0.820	-	0.864
Log Churn*	-	1.612	1.657	1.648	1.639
Expand 20%>*	-	0.903	0.886	0.896	0.942
Contract 20%>*	-	2.940	2.924	3.274	2.925
Number of Technologies	-	-	1.023	0.988	1.030
Technology-Skilled Interaction	-	-	0.986	0.987	0.986
Technology-Unskilled Interaction	-	-	1.024	1.024	1.024
Multi-Unit	1.241	1.330	1.401	1.078	1.537
SIC35	1.262	1.199	1.178	1.054	1.075
SIC36	1.031	1.189	1.145	1.088	1.149
SIC37	1.380	1.329	1.399	0.982	1.398
SIC38	1.234	1.355	1.185	1.227	1.382
Winter	0.333	0.406	0.403	0.408	0.402
Spring	1.004	1.144	1.150	1.151	1.111
Fall	1.080	1.180	1.170	1.223	1.163
Observations	36184	36184	36184	36184	36184
-2 log likelihood	576,549.6	535,685.9	536,026.1	535,546.6	531,831.1

APPENDIX B: Description of Technologies

TECHNOLOGY:

Computer-Aided Design (CAD)
Use of computers for drawing and designing parts or products for analysis and testing of designed parts and products.

CAD-Controlled Machines
Use of CAD output for controlling machines used to manufacture the part of product.

Digital CAD
Use of digital representation of CAD output for controlling machines used to manufacture the part or product.

Flexible Manufacturing Systems/Cell
Two or more machines with automated material handling capabilities controlled by computers or programmable controllers, capable of single path acceptance of raw materials an delivery of finished product.

Numerically Controlled Machines/Computer Numerically Controlled Machines
NC machines are controlled by numerical commands punched on paper or plastic mylar tape while CNC machines are controlled through an internal computer.

Materials Working Lasers
Laser technology used for welding, cutting, treating, scrubbing and marking.

Pick/Place Robot
A simple robot with 1-3 degrees of freedom, which transfer items from place to place.

Other Robots
A reprogrammable, multifunctioned manipulator designed to move materials, parts, tools or specialized devices through variable programmed motions.

Automatic Storage/Retrieval Systems
Computer-controlled equipment providing for the automatic handling and storage of materials, parts, and finished products.

Automatic Guided Vehicle Systems
Vehicles equipped with automatic guidance devices programmed to follow a path that interfaces with workstations for automated or manual loading of materials, parts, tools or products.

Technical Data Network
Use of local area network (LAN) technology to exchange technical data within design and engineering departments.

Factory Network
Use of LAN technology to exchange information between different points on the factory floor.

Intercompany Computer Network
Intercompany computer network linking plant to subcontractors, suppliers or customers.

Programmable Controllers
A solid state industrial control device that has programmable memory for storage of instructions, which performs functions equivalent to a relay panel or wired solid state logic control system.

Computers used on Factory Floor
Exclude computers used solely for data acquisitions or monitoring. Include computers that may be dedicated to control, but which are capable of being reprogrammed for other functions.

Automated Sensors used on Inputs
Automated equipment used to perform tests and inspections on incoming or in-process materials.

Automated Sensors used on Final Product
Automated equipment used to perform tests and inspections on final products.